Time varying Stock Market comovement in Europe

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ABSTRACT

Using the realised moments and panel data methods, this paper explores the impacts of EMU on time varying integration of European stock markets over the periods 1990 to 2014. This study suggests that the EMU launch has led to a significant increase in the mean value of realised correlations (i.e., a proxy for EU stock market integration) of EU stock returns. It also provides evidence that monetary convergence of the lower differentials in both interest rates and inflation rates across the sample EU countries strongly has been a key driver for the increase in integration of European stock markets since then.

Key words: Realised correlations, Stock market integration, Monetary performance convergence, EMU

JEL: E20, F36, G10, G11, G15

1. Introduction

The theoretical literature argue that integration of international or regional stock markets is linked to economic growth, macroeconomic stability, and development of financial markets through risk sharing benefits, and a reduction, spillover effects in volatility (Pagano, 1993, Osfeld, 1998, Prasad et al., 2003 among others). From a practical perspective, the study on integration among European equity markets is also very important for the following reasons. First, for international investors, an exact understanding of comovements among the European stock markets is helpful for an efficient diversification and a risk management. Second, for financial policy makers, exact knowledge of the linkages among the European stock markets may be an important concern for conducting common fiscal and monetary policies for financial stability. So, contributions from convergence among equity markets in Europe should not be underestimated.

In recent decades, most of European stock markets have experienced two major but contrasting shocks, like other kinds of financial markets (e.g., bond market, money market, etc.) in Europe. The good shock was the introduction of the Euro due to the commencement of European monetary union (EMU) on January 1, 1999, which gave a tremendous fillip to stock market integration in this region. A monetary financial institutional change such as EMU has contributed to the process of European stock market integration through a variety of channels. Given that EMU member countries share similar inflation and interest rates for a single monetary policy, this can be expected to translate into a greater similarity of discount rates to value future cash flows and hence, a higher degree of stock market convergence in Europe. Furthermore, the reduction in risk due to the removal of currency risk of exchange rate volatility within EMU and thus resultant lowering of capital costs should lead to an efficient allocation of international capital. The Euro launch to aim at tackling remaining obstacles to integration stemming from currency and regulatory segmentation was a *de facto* major milestone in the integration process. Literature has addressed that the removal of the currency risk due to the introduction of Euro fostered convergence among European stock markets for economic growth and macroeconomic stability in the region. Unfortunately it could be expected that the process of European stock market integration could have been rudely hampered by a bad shock of the recent GIIPS (i.e., Greece, Italy, Ireland, Portugal, and Spain) banking (or fiscal) crisis in 2010.

Accordingly this paper aims to shed lights on the impacts of the two shocks on dynamic integration among European stock markets by covering the longest and enough sample period 1990-2014 among the existing studies. Most extant literature has focused heavily on measuring the extent of European stock market integration driven by the EMU launch. Moreover, the literature addressing the effects of the recent EU banking crisis on the integration is still sparse as it covers only pre the crisis periods. Thus, to fill the lacuna in the literature this study examines nature and determinants of time-varying (dynamic) integration of stock markets across 14 European countries within new empirical contexts. For measuring the level of time varying EU stock market integration we use the realised moments devised by Andersen et al. (2003) and this allows us for reliable inference on the true underlying latent volatility in the stock return series. Its drivers are captured by using panel data techniques to effectively control for an unobserved heterogeneity across cross sectional and time series units. Literature that systematically investigates the impacts of both EMU and the recent EU banking crisis on stock market integration in Europe is still limited to few.

For explaining dynamic integration of European stock markets, this paper mainly focuses on analyzing the roles of monetary performance convergence between sample (pairwise) countries. For this purpose, this study uses interest rate and inflation differentials as proxies for monetary performance convergence of pairs of countries. This enables us to effectively examine direct impacts of the monetary convergence among sample countries for integration of European stock markets. For reference, the extant literature uses only a single monetary performance variable in each country (Baele, 2005; Fratzscher,2002) or monetary convergence variables *vis-à-vis* German or Euro area weighted averaged monetary performance (Kim et al., 2005). Another novelty of this study is that it tries to test for the panel causality between EU stock market integration and EMU in the panel data format that allows us to effectively account for a latent heterogeneity problem. This would be one of the first among the literature. Kim et al. (2005) report the causality individually for their sample European countries.

This paper is structured as follows. Section 2 reviews the existing literature of examining time varying integration of European stock markets. Section 3 explains an analytical background and empirical methodologies for this study. Section 4 describes data used. Section 5 discusses empirical results. Section 6 briefly concludes.

2. Literature on time varying integration of European stock markets

This section reviews the extant literature that investigates dynamic integration of European stock markets. With very few dealing with the impact of the recent EU fiscal crisis on it, most studies have devoted to exploring the effects of EMU on integration of European stock markets.

2.1International asset pricing approach to the EMU impact

One strand of the empirical literature takes a structural form approach by working within an international asset pricing framework. For instance, Hardouvellis et al. (2006) analyse integration of EU stock markets pre EMU by allowing European stock market returns to be exposed to an idiosyncratic risk factor, an EU risk factor, and a currency risk factor. They suggest that the extent of EU stock market integration (with the global European index) is positively related to the markets' perception of the probability that the country will join in EMU, where the latter is measured by forward interest rate differential with Germany. European stock markets converged in the second half of the 1990s although the extent of integration shows ups and downs. For the period 1985-2002 Brooks et al. (2004) detect an increase in integration of western European stock markets since the mid-1990s. However, they argue that the increased sectoral integration among the markets is due to a temporary phenomenon connected with the TMT (Technology, Media, and Tele-comunication) bubble. Compared to the substantial body of studies on the effect of the EMU launch on European stock market integration, the literature associated with the effect of the European fiscal crisis in 2010-2011 is extremely sparse. Exceptionally, over 1990-2012 period of including the recent EU fiscal crisis, a significant study of Bekaert et al. (2013) provides a comprehensive approach to measure stock market integration among European countries. Their study is based on average industry earnings yield differences under the assumption that industry yields converge in financially integrated markets. They address that the membership of joining in EU increased financial integration among European countries post as well as pre the crisis.

2.2 Time-varying second moments approach to the impact of EMU

The other approach of the literature concentrates on time varying second moments of the stock return series. A majority of the studies have primarily relied on time-series techniques such as the GARCH (family) models, Markov switching models, cointegration models in terms of returns, variances, and covariances.

For instance, a study of Morana and Beltratti (2002) finds empirical evidence on the positive impact of the Euro's introduction on integration of five European stock markets through the Markov switching models for returns and volatilities. Their study reports that post EMU, the increased spillovers of return volatilities across European stock markets is mainly due to a stabilisation of fundamentals for traditionally unstable European countries (e.g., Italy, Spain) through the removal of exchange rate volatility. In order to extensively study dynamic integration of EU stock markets, Cappiello et al. (2006) use an asymmetric DCC (Dynamic Conditional Correlation)-GARCH model. They address that upon the creation of the unified currency in Europe, a significant structural break was found in the level of conditional correlations but not in the level of conditional volatilities for 13 European stock markets. In particular, the conditional stock correlations for the major EU stock markets such as France, Germany, Italy and the UK have significantly increased since then.

In contrast, Baele (2005) using the regime-switching GARCH model shows that stock return variances in the Euro area are increasingly explained by common European shocks. However, his study indicates that the rise on integration of European stock markets mainly took place during the second half of the 1980s and the first half of the 1990s, implying the effect of EMU on the market convergence is limited as in Berben and Jansen (2005). In addition, he suggests that stock market development, trade integration, and price stability stimulate the stock market integration. In the similar line, Berben and Jansen (2005) using a GARCH model with a smoothly time varying conditional correlation find that the EMU commencement appears to have hardly influenced the pace of stock market integration within Europe. This may imply that much gain was realised in the late 1980s and early 1990s in advance.

To extending the literature on primarily measuring the degree of EU stock market integration, Fratzscher (2002) using the trivariate GARCH find that post EMU, stock markets in the Euro zone area appear to be highly integrated due to the removal of exchange rate uncertainty. Additionally, his research suggests that to some extent, a monetary policy convergence (e.g., inflation rates and nominal short-term interest rates) vis-à-vis Germany has been a driving force behind the financial integration process. Along a similar vein, Kim et al. (2005) by splitting the analysis into two stages report significant evidence on integration of EU stock markets driven by the EMU launch. By applying the EGARCH framework, they show that integration of stock markets in Europe was highly volatile prior to the second half of the 1990s and has increased rapidly in the two years leading up to the official launch of the Euro. Since then, the process of integration among the markets has been much stronger and more stable than before. Importantly, the authors find that the correlation (with Euro area weighted averages) in consumer price inflations used to proxy monetary convergence has been an important factor behind higher levels of comovements between the EMU countries and the US. However, the correlation in nominal short term interest rates has been significantly beneficial for only one country, Italy. Very recently, Mylonidis and Kollias (2010) using the cointegration technique assess the dynamic process of convergence among major four European stock markets (Germany, France, Spain, Italy) in EMU in the post euro era of January 1999 and July 2009. They find evidence that among the four stock markets, the German and French markets seem to have experienced higher convergence while the dominant position of Germany seems to be affirmed by their test.

To summarise, all the studies above depend on a multi stages method by splitting the analysis into different stages (2 or 3 stages) to investigate a relation between EU stock markets integration and EMU. However, a multi–stage estimation procedure may lose some efficiency of estimation since sampling errors from pre estimation stages are omitted at the next stage and so the standard errors may be smaller than the true ones.

Eventually, this method may lead to biased results and then researcher should consider this when interpreting results. To overcome this problem, we employ a panel data analysis technique with realised correlations to investigate dynamic integration of European stock markets with a particular emphasis on the periods following the wake of EMU.

3. Analytical background and Empirical Methodologies

3.1 Analytical background

Using the factor model proposed by Ross (1976) we briefly present an analytical background for supporting the relationship between monetary performance similarities (or differentials) and (European) stock return corrleations among pairwise countries.

Given that there are K factors $F_1, F_2, \cdots, F_K$ affecting the stock returns R_A and R_B for country A and country B, resepectively, we can consider the following factor models by Ross (1976):

$$R_A = \alpha_A + \sum_{i=1}^{K} \beta_{Ai} F_i + \varepsilon_A \tag{1}$$

and $$R_B = \alpha_B + \sum_{i=1}^{K} \beta_{Bi} F_i + \varepsilon_B \tag{2}$$

where $\forall i \neq j, Cov(F_i, F_j) = 0$, $\forall i, Cov(F_i, \varepsilon_A) = 0$, $\forall i, Cov(F_i, \varepsilon_B) = 0$, and $Cov(\varepsilon_A, \varepsilon_B) = 0$. Then, we have

$$Cov(R_A, R_B) = \sum_{i=1}^{K} \beta_{Ai} \beta_{Bi} Var(F_i) \tag{3}$$

or $$\rho_{A,B} = \sum_{i=1}^{K} \beta_{Ai} \beta_{Bi} \frac{\sigma_i^2}{\sigma_A \sigma_B} \tag{4}$$

where, $\sigma_i^2 = Var(F_i)$, $\sigma_A = \sqrt{Var(R_A)}$, $\sigma_B = \sqrt{Var(R_B)}$, $\rho_{A,B} = \dfrac{Cov(R_A, R_B)}{\sigma_A \sigma_B}$.

Then, we have

$$\forall k \in \mathrm{N}_K, \frac{\partial \rho_{A,B}}{\partial \sigma_k} = \beta_{Ak}\beta_{Bk}\frac{2\sigma_k}{\sigma_A\sigma_B} = \begin{cases} > 0, & if \;\; \beta_{Ak}\beta_{Bk} > 0; \\ < 0, & if \;\; \beta_{Ak}\beta_{Bk} < 0. \end{cases} \tag{5}$$

We can see that the same change of the common risk (the future uncertainty of the common factor) can either increase or decrease the stock return correlation between the two countries depending on whether the common factor has similar or opposite effects on the stock returns of the two countries.

For example, assume that country A is an oil producer while country B is an oil consumer. Then, it is obvious that the oil price commonly affects the stock returns of the two countries in the opposite directions. That is, letting F_k be the oil price, we will obviously have $\beta_{Ak} > 0$ and $\beta_{Bk} < 0$. In that case, we will have

$$\frac{\partial \rho_{A,B}}{\partial \sigma_k} = \beta_{Ak}\beta_{Bk}\frac{2\sigma_k}{\sigma_A\sigma_B} < 0 \tag{6}$$

implying that the increasing volatility of the oil price will make the stock returns of the two countries diverge from each other.

Meanwhile, if both countries are exporting to the U.S. so that their stock returns are both influenced by the U.S. stock market return in a similar manner, then letting F_k be the U.S. stock market return, we will have $\beta_{Ak} > 0$ and $\beta_{Bk} > 0$. Then, we will have

$$\frac{\partial \rho_{A,B}}{\partial \sigma_k} = \beta_{Ak}\beta_{Bk}\frac{2\sigma_k}{\sigma_A\sigma_B} > 0 \tag{7}$$

implying that the U.S. stock market risk increase can make the stock returns of the two countries converge to each other.

For further simplicity, let us assume single factor (market) models for the two countries:

$$R_A = \alpha_A + \beta_{AM} R_M + \varepsilon_A \tag{8}$$

and $R_B = \alpha_B + \beta_{BM} R_M + \varepsilon_B$ (9)

where $Cov(R_M, \varepsilon_A) = 0$, $Cov(R_M, \varepsilon_B) = 0$, and $Cov(\varepsilon_A, \varepsilon_B) = 0$. Then, we have

$$Cov(R_A, R_B) = \beta_{AM} \beta_{BM} Var(R_M) \tag{10}$$

or $\rho_{A,B} = \beta_{AM} \beta_{BM} \dfrac{\sigma_M^2}{\sigma_A \sigma_B}$ (11)

where, $\sigma_M^2 = Var(R_M)$, $\sigma_A = \sqrt{Var(R_A)}$, $\sigma_B = \sqrt{Var(R_B)}$, $\rho_{A,B} = \dfrac{Cov(R_A, R_B)}{\sigma_A \sigma_B}$.

Here, R_M reprsents the global market portfolio. Then, we have

$$\frac{\partial \rho_{A,B}}{\partial \sigma_M} = \beta_{AM} \beta_{BM} \frac{2\sigma_M}{\sigma_A \sigma_B} = \begin{cases} > 0, & if \;\; \beta_{AM} \beta_{BM} > 0; \\ < 0, & if \;\; \beta_{AM} \beta_{BM} < 0 \end{cases} \tag{12}$$

implying that in the case σ_M increases due to a global financial crisis, the stock market correlation $\rho_{A,B}$ between the two countries increases if both of them are affected by the global financial market (e.g., the global market portfolio) in the same direction and it decreases otherwise.

Of course, these models are only based on factor models for stock returns. Since there may be some additional factors influencing only the covariance or the correlation of the two different stock returns not influencing the corresponding individual stock returns, we can build up our regression model as follows:

$$Cov(R_A, R_B) = \alpha_{AB} + \sum_{i=1}^{K} \beta_{Ai} \beta_{Bi} Var(F_i) + \sum_{j=1}^{L} \beta_j G_j + \varepsilon_{AB} \tag{13}$$

or $\rho_{A,B} = \dfrac{\alpha_{AB}}{\sigma_A \sigma_B} + \sum_{i=1}^{K} \beta_{Ai} \beta_{Bi} \dfrac{\sigma_i^2}{\sigma_A \sigma_B} + \sum_{j=1}^{L} \beta_j \dfrac{G_j}{\sigma_A \sigma_B} + \dfrac{\varepsilon_{AB}}{\sigma_A \sigma_B}$ (14)

where, $\sigma_i^2 = Var(F_i)$, $\sigma_A = \sqrt{Var(R_A)}$, $\sigma_B = \sqrt{Var(R_B)}$, $\rho_{A,B} = \dfrac{Cov(R_A, R_B)}{\sigma_A \sigma_B}$.

Here, the G_j s represent those additional factors influencing only the covariance of the two different stock returns other than the $Var(F_i)$s.

The problem is that we do not exactly know what those common international risk factors are. And even if we know those factors F_i s correctly, we cannot easily measure their future uncertainty σ_i due to data availability. Actually, we at least need weekly data for those (assumed-to-be-known) risk factors to calculate the annual σ_i s because a year usually consists of 52 weeks or so and we usually need at least 30 observations to compute any statistics.

But fortunately, it is highly probable that if the two countries have similar economic (monetary) structures, then they will have a higher chance to be affected by those unknown common international risk factors' future uncertainty in a similar manner. That is, if country A and country B have similar industrial structures consuming massive oil, then both of them will be affected by the future uncertainty of the international oil price (a common risk factor) in the same direction. Then, the rise of the future oil price uncertainty will increase the stock return correlation. This implies that similar macroeconomic (monetary) variables of two countries will result in higher stock return correlation between the two. So our research will focus on how similarity (convergence) of the two monetary performance variables (i.e., interest rate and inflation differetinals) between pairs of our sample countries in Europe will influence the stock return correlation between them post EMU.

3.2 Empirical Methodologies

3.2.1 Measuring integration of European stock markets

In general, the traditional procedures such as parametric GARCH, stochastic volatility model, or implied volatility analysis for estimating do not allow for reliable inference on the true underlying latent volatility in sample data. To overcome this problem, the *ex post* realised variances and correlations obtained by summing the squares and cross-products of high frequency returns are a good alternative. Then volatility and correlation estimates so constructed are model free and they also are, in theory, free from a measurement error as the sampling frequency of the returns approaches infinity (Andersen et al., 2001a). This econometric merit of realised variance and correlation motivates our use of this method.

The realised correlation measure was introduced by Andersen et al. (2003) and it is based on the availability of higher frequency data to obtain a consistent estimate of correlation at lower frequency. Whilst Andersen et al. (2003) use intra-daily data to measure daily realised correlations, Beine and Candelon (2009) and Cipollini et al. (2015) use daily observations to measure annual realised correlations in their study. This study computes annual estimates of the realised pairwise correlations, using daily data of stock returns. In this paper daily stock returns are defined as $r_{i,t,d} = \ln(p_{i,t,d} / p_{i,t,d-1}) \times 100$ where p are stock indices. The measure of realised variance is given by

$$\sigma_{t,i}^2 = \sum_{d=1}^{D_t} [r_{i,t,d}]^2 \tag{15}$$

where $p_{i,t,d}$ are values of the stock index of country i at t ($t = 1,...,22$ and day d ($d = 1,..,D_t$) . D_t is total business days in the year t and the total number of years is 22. In line with Andersen et al. (2003) we need to assume $E(r_{i,t,d} r_{i,t,d-1}) = 0$ or the stock market efficiency. Next, applying the similar method this study measures realised covariance between the annual stock returns of country i and country j as

$$\sigma_{ij,t} = \sum_{d=1}^{D_t} [r_{i,t,d} \times r_{j,t,d}] \tag{16}$$

Finally, the realised correlation $\rho_{ij,t}$ measure is obtained as:

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{i,t}^2 \times \sigma_{j,t}^2}} \tag{17}$$

Following Beine and Candelon (2009) and Cipollini et al. (2015), this study also employs a Fisher-Z transformation of $\rho_{ij,t}$ to free the panel regression from bounds on the predicted realised correlations:

$$\overline{\rho_{ij,t}} = \ln(\frac{1+\rho_{ij,t}}{1-\rho_{ij,t}}) \tag{18}$$

Based on equation (3), given 14 countries under investigation this paper estimates 91 unique pair-wise realised correlations for each year. Given 25 annual observations, our dataset consists of 2275 observations for realised correlations.

An inspection of Figure 1 below, where the pairwise (Z Fisher transformed) realised correlations are plotted, exhibits an upward trend especially after the Euro's introduction as single currency in Europe albeit not in a monotonic fashion. This suggests an increase in the degree of time-varying EU stock market integration. Meanwhile, it also shows a decline in several pairs around the end of the sample period. This presents that many of the stock markets in Europe visually turned toward decoupling around 2010.

[Figure 1 around here]

3.2.2 Panel estimation

To examine determinants of European stock market integration this paper relies on the use of panel data techniques to control for unobserved heterogeneity across cross sectional units. The panel model specified in this study is

$$\overline{\rho_{ij,t}} = \alpha + \delta_{ij} + \alpha D_{EMU} + \beta_2 X_{ij,t} + \beta_3 X_{ij,t} D_{EMU} + \gamma C + \eta D_{GIIPS} + \varepsilon_{ij,t}$$

$$(i \times j) \in [1,..,N(14)], \qquad i < j, \quad t = 1,..,T(25) \tag{19}$$

where the dependent variable $\overline{\rho_{ij,t}}$ is realised correlations (hereafter, correlation) over time, α is a constant, δ_{ij} represents (time-invariant and unobserved) cross-section effects, which can be fixed or random, and $\varepsilon_{ij,t}$ is the error term over time. D_{EMU} represents an EMU intercept dummy with values of 0 up to 1998 and 1 from 1999 onwards. $X_{ij,t}$ is a vector of two exogenous explanatory variables of the inflation differentials and (short term) interest rate differentials proxied for monetary performance convergence among sample countries. D is a vector of interactive slope dummies that includes D_{EMU} on the two explanatory variables and C is a vector of control variables. Finally, D_{GIIPS} denotes an intercept dummy of the GIIPS banking crisis that takes values of 1 over years 2010-2011 and 0 otherwise.

In this paper, the time series dimension T is equal to 25 (annual observations) and the cross-section dimension N is given by ($\frac{14 \times 13}{2}$), which equals 91, that is, the number of unique annual pairwise realised correlations among 14 EU stock markets. In principle the annual realised correlations considerably relieve a microstructure noise daily problem which is likely to arise at higher frequency (e.g., in presence of intra-data). Given that daily stock indices are used to obtain annual realised correlations, this study argues that the 260 observations employed each year allow us to obtain a good proxy of the true correlation (at one year horizon).

For regression estimations, this paper runs the fixed effects (FE), random effects (RE) models and the pooled OLS model, respectively. We use the OLS (ordinary least squares) method for the fixed effects model and GLS (generalised least squares) method for the Random effects model, respectively. To assess which panel model is statistically appropriate, the Breusch and Pagan Lagrange Multiplier (*LM*) and Hausman tests are employed. For a diagnostic test, we account for the problem of *CSD* between error terms in panel data sets. For a robustness, this study checks for endogeneity bias by using an instrumental variable (IV) estimation for our benchmark results. This study also explores an effect of a persistence of the dependent variable by running dynamic panel regressions with AR (1) of the realised correlations in each panel specification. Lastly, applying the (traditional) pairwise Granger causality and panel VAR methods, we analyse the panel causality between European stock market integration and EMU.

4. Data Issues

4.1 Stock Return Data

In order to study the linkages among European stock markets this paper uses daily stock returns for total 14 European countries from 1st January 1990 to 29th December 2014. These include the 11 Euro-zone countries (i.e., Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain) that have adopted the Euro as a common currency and the 3 non Eurozone but major EU countries (i.e., Denmark, Sweden, and the UK) that have not adopted the Euro. Note that we exclude 7 new Eurozone countries of Cyprus, Estonia, Latvia, Lithuania, Malta, Slovakia, Slovenia whose time gaps between the EMU launch in 1999 and their respective EMU memberships over the very recent periods 2008-2014 are considerable. In addition, Luxembourg, one of initial EMU member states, is also exclusive due to unavailability of data of stock return and interest rate for the full sample period. All the national stock market indices used in this paper are available from the Datastream International and are given in a US dollar unit.

The national stock market (continuously compounded) returns used in the study are computed as the log of changes in the closing index levels from one trading day to the next day such that $r_{i,t,d} = \ln(p_{i,t,d} / p_{i,t,d-1}) \times 100$ for the stock market i at year t ($t = 1,..,25$) and day d ($d = 1,...,D_t$) where D_t is the total number of business days (260) in individual year t.

4.2 Variables

4.2.1 Exogenous Explanatory Variables

In the extant literature macroeconomic (monetary) factors such as inflation and interest rate have been effectively proposed to explain international stock market linkages (e.g. Baele, 2005, Beine and Candelon, 2006, Morana and Betratti, 2002 and Kim et al., 2005). Moreover, the EMU process has been characterised by monetary policy convergence such as short term interest rate and inflation in that a single monetary policy for all EMU members has replaced independent monetary policies of each EMU country. For example, Fratzscher (2002) and Kim et al. (2005) show that monetary policy convergence via inflation and short term interest rates in Europe have been the central drivers behind the EU stock market integration process. Therefore, we can a priori expect that the monetary policy convergence of inflation and short term interest rate differentials between EU countries will stimulate higher integration of EU stock markets.

In line with Beine and Candelon (2006) this paper employs annual interest rate and inflation differentials of pairs of sample EU countries to proxy EMU convergence. Since this study focuses on low frequency financial integration it uses annual realised correlations for the dependent variable and also annual observations for each explanatory variable.

a. Inflation Differentials

The first explanatory variable is the inflation differentials between pairs of the sample countries. They are computed as differences in the growth rate taking logarithm of consumer price indices (CPI) of each country. Note that this paper uses absolute value for this variable rather than the actual difference because our concern is not about which country's inflation rate is higher but about how large the differential is (Pretorius, 2002; Beine and Candelon, 2009). The CPI for each country is composed of annual observations from the OECD-MEI (OECD-Main Economic Indicators) database for the full sample period.[2] This study expects the sign of the slope coefficient for this variable to be negative (-). More specifically, the lower differentials between pairs of countries would proxy higher degree of monetary policy convergence and then, this would impact positively on EU stock market integration.

b. Interest Rate Differentials

The other explanatory variable is the short term interest rate differentials between two countries. The interest rates in the study is 3-month interest rates in all the sample countries at the annual frequency. The interest rate differentials between the pairwise countries are computed as the simple difference between the short term interest rates of pairs of countries. Along the same vein with the inflation differentials, this paper uses absolute value for the inflation differentials among the sample countries. The interest rates data are also available from the OECD-MEI database. Note that for periods 1990-1994 only, the interest rates of Greece are not available from the same source and so, we replace ones from Datastream International for the missing values. Similarly to the case of the inflation differentials variable, we can expect the sign of the slope coefficient for the interest rate differential to be negative (-). This means that lower differentials

[2]The OECD-MEI has published yearly short term interest rates and consumer price index (CPI) of all member countries every year.

between pairs of countries have a positive effect on the integration.

4.2.2 Dummy Variables

a. Dummies Associated with EMU

Our panel models allow two EMU dummies to be considered. The first is a time dummy related to the introduction of the Euro in Europe, capturing an intercept shift. The second is the EMU slope dummies interacting with the inflation and interest rate differentials. Both have values of 1 from 1st January 1999 and 0 otherwise.

In particular, the EMU intercept dummy is used to capture the direct impact of EMU, the elimination of exchange rate risk, on integration of European stock markets. The EMU slope dummies for the two explanatory variables proxying monetary policy convergence are used to analyse the potential impacts of monetary policy convergence on the integration post EMU. We can expect that the EMU intercept dummy has a positive effect (+) on the integration while the EMU slope dummies have negative one (-).

b. EU Banking Crisis Dummy

To examine an impact of the GIIPS banking crisis in 2010-2011 on integration of European stock markets this paper includes another time dummy of capturing an intercept shift that takes value 1 over the years 2010-2012 and 0 otherwise in the panel models. This dummy is expected to have a negative effect on the integration which suggests a decoupling effect in unstable times.

4.2.3 Control Variables

This paper uses a variety of control variables to effectively examine the effects of monetary performance convergence on integration of stock markets in Europe. The variable *IP_Dif* denoted for industrial production differentials is used to control a difference of economic activity (growth) among sample countries. For this, we use absolute value of difference of industrial production indices between sample countries. The industrial production indices of the sample countries are gathered from the OECD-MEI database. The variable *VDAX* (the implied volatility of DAX equity index option) is used to examine an effect of market participants' expectation for a future stock market uncertainty in the region on the market integration. To control for the effect a rate of global risk-free return this paper uses a short term interest rate of 3-month US treasury bill denoted by *US-Tbill*. The data frequency for these exogenous variables is based on annual to match the frequency of the dependent variable. The raw data for *VDAX* and 3-month *US-Tbill* are available from the Datastream international and those for the industrial production differentials among sample countries are available from the OECD-MEI database.

Table 1 presents the descriptive statistics and panel structure of the exogenous independent variables used for this study. We need to concentrate on the median rather the mean because the two explanatory variables show a skewed distribution. In Table 1, the median of the (short) interest rate differentials is some 0.3 over the full sample period and the corresponding figure of inflation differentials is around 0.009. These figures may ensconce some variation over time. The kurtosis of both variables also shows high figures that present a feature of the leptokurtic distribution gathering heavily toward the centre. The skewness and kurtosis of non-normality for both are also shown in the whole control variable.

[Table 1 around here]

Prior to our actual panel regression analyses, we conduct the IPS-panel unitroot test devised by Im, Pesaran and Shin (2003) to check for stationarities of all the level series.[3] The results are reported in Table 2. The IPS statistics strongly reject the null of the unit root in all the series at a significance level of 1%. This suggests that both the dependent variable of realised correlations and the whole exogenous independent variable are stationary over time.

[Table 2 around here]

Table 3 shows the results of correlation matrix across all the independent variables. Overall, the low correlation estimates across them suggest that except a relatively high value (0.6649) between interest rate and inflation differentials, there causes no serious correlation problem although they are simultaneously estimated in our panel regressions.

[Table 3 around here]

5. Empirical Results

5. 1 Benchmark Results of Panel Regressions

This subsection analyses the main results of the panel data regressions with fixed effects and with random effects.[4] Table 3 shows the static panel regression results for determinants of European stock market integration over the full sample period 1990-201.

The *LM* (Lagrange Multiplier) test proposed by Breusch and Pagan (1980) is used for comparing the simple pooled OLS and RE models. All the *LM* statistics (2290.44, 2306.70, 2203.53, 2087.87, 1863.32 and 1755.25) for the whole Regression in Table 3 far exceed the 95 percent significance level for the $\chi^2_{(1)}$ distribution. So, this suggests

[3]We check that the Fisher type test of by Maddala and Wu (1999) based on combining the significance levels of the different tests makes the similar results with those of the IPS tests. The specific are omitted to account for space but available upon request.

[4]Both the time-varying (Z Fisher transform) realised correlations across stock returns and differentials of the two monetary variables across two countries are computed using MATLAB Version 6.5 and the various panel data regressions are conducted using STATA Version 13.

that the RE models for all the regression specifications are preferred to the pooled OLS regression models. To test for whether the coefficients by the efficient RE estimator are equal to the ones estimated by the consistent FE estimator, this paper employs the Hausman test. Most of the Hausman statistics (15.83, 57.40, 30.00, 30.71 and 205.51) in Table 3 do reject the null at the standard level except for the insignificant value (7.71) of Regression 3 suggesting a preference of the RE model. Hence, this study focuses on the results obtained by the FE models.

[Table 4 around here]

First of all, as for the EMU effect on integration of European stock markets, all the FE panel regressions (Regressions 1, 2, 4, 5, 6) and one RE panel regression (Regression 3) on Table 3 estimate highly significant and positive coefficients at 0.750, 0.854, 0.882, 0.972, 0.915, 0.977, respectively, for the EMU intercept dummy (D_{EMU}). The result suggests that the exchange rate stability due to the Euro's introduction has significantly stimulated integration among stock markets in Europe. This is in line with the extant literature of Fratzscher (2001), Morana and Beltratti (2002), Kim et al. (2005) and Cappiello et al. (2006) that address the EMU launch has contributed to an increase in convergence across European stock markets. However, this result diverges from that of Berben and Jansen (2005) and Baele (2005) that suggest the event has a limited impact on the integration. Bekaert et al. (2013) also argue that the EU membership is an important factor for explain integration of economic and financial integration rather than the Euro' introduction. The recent banking crisis caused by the European GIIPS countries shows a statistically significant positive effect on the market integration because the EU banking dummy (D_{GIIPS}) has highly significant positive coefficients on the whole specification. One possible explanation for this counterintuitive result would be due to transient volatility spillover effects rather than return spillover ones among

EU stock markets during the banking crisis**.**

Regarding the effects of monetary performance convergence across the sample EU countries, Regressions 1, 3, 5, and 6 estimate insignificant coefficients for the interest rate differentials at all but do highly significant negative ones for the EMU slope dummy interactive with this variable. The results address that pre EMU, interest rate differentials between EU countries were not associated with an increase in integration of European stock markets but post EMU, the differentials have significantly driven an increase of the market integration. Overall, these findings on the interest differentials variable goes against Fratzcher (2002) who suggests that short term interest rates have been a driving force behind the EU stock markets integration process pre EMU. Baele (2005) also suggest that interest rate (monetary) convergence intensified European shock spillover in the second half of the 1980s and the first half of the 1990s before the EMU launch. For the post EMU period, Kim et al. (2005) and Morana and Beltratti (2002) argue that the effect of short interest rates has been limited to just some country (e.g., Italy) unlike our finding. Along a similar vein, the panel Regressions 2, 4, 5 and 6 with fixed effects estimate the effects of inflation (CPI) differentials, the other proxy for monetary performance convergence across sample EU countries on the stock market integration in Europe. Pre EMU, the panel regressions show mixed results on the inflation differentials variable. That is, Regressions 2 and 6 estimate significant positive coefficients on this variable before EMU but Regressions 4 and 5 do insignificant ones. Note that the significant values estimated by Regressions 2 and 6 would be biased due to a very possible problem of a cross sectional dependence (*CSD*) across errors in cross sectional units. We specifically address this issue on Table 6 later. Meanwhile, the three panel Regressions 2, 4 and 6 show significantly big negative estimates (-10.467, -7.390, -8.520) at the 1% level for the EMU slope dummy on this variable. The results suggest that pre EMU, the inflation (monetary) performance similarity (i.e., the lower inflation differentials) among the sample EU countries had no influence on the market integration in Europe but had a significant influence post EMU. In association with the findings, the extant studies of Baele (2005), Fratzscher (2002), Kim et al. (2005) and Baekaert et al. (2013) argue that price stability (CPI) is an important factor for European stock market integration. It could be addressed that the results obtainable from our empirical tests for the post EMU periods are, overall, line with our theoretical expectation argued previously for this study.

The effects of control variables are shown on Regressions 3, 4, 5 and 6. No regressions estimate significant values for the industrial production differentials (*IP_Dif*) variable. This suggests insignificant influence of the economic growth differentials between sample countries on integration of EU stock markets.[5] Meanwhile, the VDAX has significant negative estimates on the market integration and then this suggests that an investors' low expectation for future financial market uncertainty is associated with the market integration in this region. In general, market participants are inclined to increase their portfolio with stocks of risky asset (bonds of safe one) when an uncertainty for future economy is low (high). Lastly, the four regressions estimate significant negative coefficients for the global risk free rate of return (*US-Tbill*) proxied by the 3month-US treasury bill. The results address that a lower global risk free rate of return contributes to an increase in integration of EU stock markets. This may imply that investors are likely to increase their portfolio with stock assets of risky ones in this region when the global riskless rate of return is low. We analyse other possible control

[5]We also found insignificant coefficients for the EMU slope dummy interactive with this *IP_Dif* variable at all, whereby suggest no influence of real economic activity similarities among sample countries on convergence of European stock markets post EMU. The specific results are untabulated but ready to any request.

variables such as stock turnover and market captalisation differentials(i.e., proxies for stock market similarities) among sample markets for the available periods of 1990-2012 only. However, both make no significant effects and so, our main results remain valid still.[6]

5.3 Endogeneity bias test using instrumental variables

This study tries to check for endogeneity biases on the estimates obtained from the panel regressions in Table 4 by using instrumental variable (IV) estimation where the instruments are proxied by the 1st lags of the two monetary convergence variables. In line with all the panel regression models in Table 4 of reporting benchmark results in this study, Table 5 presents results for the whole model with the instrumental variables.

The results in Table 5 show that the empirical findings for the full sample period are fundamentally identical to the ones (in Table 4) previously discussed which ignored an endogeneity biases. Hence, our results in Table 4 are confirmed although we consider a possibility of endogeneity biases in our panel regressions. In addition, all the Hausman statistics in Table 5 also support the panel model with fixed effects as the best fit to the data because the test statistics strongly reject the null hypothesis at the 1% significance level, respectively. In particular, the highly significant Hausman statistic (140.00) for Regression 3 in Table5 also suggests the FE model for the most appropriate model unlike the case supporting the RE model for Regression 3 in Table 4 discussed previously.

[Table 5 around here]

5.4 Diagnostic Test for Cross Sectional Dependence

5.4.1 Pesaran Test

[6]The specific results are omitted for matters of unmatching with the variables available for the full sample period and saving space but available upon request.

It is a standard assumption that the error terms across cross section units in panel data specifications are independent for an accurate a panel data analysis. In reality, to ensure that a statistical inference of the panel analysis is valid, a diagnostic test for cross sectional dependence (CSD) across error terms of cross-section units in each panel context of cross sectional time-series datasets, LM (Lagrange Multiplier) test statistics proposed by Breusch and Pagan (1980) satisfies with valid and desirable statistical properties for cross sectional dependence test. In contrast, when the form of large N and small T ($N > T$), which is more common in context of the panel data sets, the LM test does not enjoy any desirable statistical properties any more in that it may exhibit substantial size distortions. Specifically, for a finite T, E ($T\hat{\rho}_{ij}^2 - 1$) will not inclined to be correctly centeralised at zero (here, $\hat{\rho}_{ij}^2$ is the sample estimate of the pair wise correlation of the residuals) and the incorrect centering the LM statistic with large N is likely to be accentuated. Eventually the incorrect centering may cause the serious problem of size distortions that tend to get worse with large N (Pesaran, 2004; Sarafidis et al., 2006).

For the purpose of testing the null of CSD in panel models with such a form of $N > T$, Pesaran (2004) suggests a parametric procedure, so called, Pesaran test, well handling unbalanced as well as balanced panels. The statistic of Pesaran test follows a standard distribution as well. (see Hoyos et al., 2007). So, in Table 4 above, all the pesaran statistics across error terms in the whole panel model strongly rejects the null of no CSD at a 1 % significance level. This result implies an obviously high possibility of CSD across the error terms. Nevertheless, erroneously ignoring the CSD across error terms can make the estimators inconsistent and eventually lead to seriously biased results in the estimation of panel models. Hence, it is crucial to overcome the problem such as cross sectional correlations in panel models for an accurate study on integration of European stock markets driven by the EMU launch. We more discuss this issue at the next subsection.

5.4.2 Fixed Effects Regression with Driscoll-Kraay Standard Errors

A growing body of literature in panel data study comes to the conclusion that panel data sets are likely to exhibit the substantial CSD between error terms (see Robertson et al.,2000; Pesaran, 2004; Anselin, 2001; Baltagi, 2005 among others). According to those studies, CSD in panel models may rise due to a presence of common shocks and unobserved components as well as idiosyncratic pairwise dependence in the disturbances.

To effectively account for the CSD problem between error terms in panel data sets, conducting the fixed effects regression of panel data with the Driscoll and Kraay standard errors may be a good diagnostic test. Specifically, by running Monte carlo simulation, Driscoll et al. (1998) and Hoechle (2007) compare the finite sample properties of CSD–consistent Driscoll-Kraay estimator (considering CSD) with the properties of other, more commonly used covariance matrix estimators of residuals not accounting for CSD. Importantly, their studies address that Driscoll-Kraay standard errors are well calibrated even when cross sectional correlation is present. Our study, therefore, conducts the FE analysis of panel data with Driscoll-Kraay standard errors for an additional diagnostic test on the CSD captured in FE models through the Pesaran test above.

Table 6 well reports the results for the FE regressions applying Driscoll-Kraay standard errors method. In Table 5, first of all, the F-value testing the joint significance of all the explanatory variables well rejects the null, $\forall\_H_0 = 0$ (i.e. the estimated coefficients are all 'zero') at the 1% significance level and a maximum lag is 2 providing for the most desirable estimates.[7] The fundamental patterns of the coefficients in Table 6 are almost identical to those in FE models with robust errors in Table 4. The only exception is on those of the inflation differentials (*InfDif*) variable pre EMU on Regression 2 and 6. As discussed earlier, the positive values on Table 4 might be biased due to a possibility of the CSD in panel data. Overall, the results in Table 5 confirms a preference of the results from the FE model despite the presence of the *CSD* in the panel data specifications. Exceptionally, we need to address that the *CSD* test for Regression 3 supporting panel model with random effects in Table 4 is now unfeasible. Even if so, our benchmark results remain valid still.

[Table 6 around here]

5.5 Dynamic Panel Regression Results

To examine an effect of a persistence of the dependent variable on EU stock market comovement we specify a dynamic panel model with AR(1) of the dependent variable (i.e., realised correlations) in each panel specification.

The results are reported in Table 7. Overall, the estimation results obtainable from the dynamic panel models are qualitatively similar with the benchmark results obtainable from the static panel models in Table 4 not only for our main explanatory variables but also the other exogenous control variables. All the robustness and diagnostic tests for the dynamic panel regression results also showed statistically economically similar results with the ones from the various tests for our benchmark

[7] For selecting a lag length $m(T)$, the study applies for a simple heuristic taken from the first step of Newey-West's (1994) plug-in procedure and the heuristic applied sets $m(T) = floor[4(T/100)^{2/9}]$. Our panel regressions by selecting a long range of several lags 1-9 also estimated similar coefficients with the regressions with lag 2. The specific results areomitted but ready to any request.

results from the static panel regressions, respectively.[8]

[Table 7 around here]

5.6 Granger Causality Tests

It would be worthwhile to investigate a predictive causality between EU stock market integration and EMU. Ordinarily, the (panel) regressions merely address impacts of explanatory variable on dependent one in the model. So, this subsection discusses the causality between EU stock market integration (i.e., the Z-transform realised correlations) and EMU (i.e., the EMU intercept dummy) by using the traditional pairwise Granger causality test and the VAR test on our panel data. The results for the former test are reported in Table 8. Interestingly, all the Granger causality statistics for the two variables of interest in Table 8 strongly reject the two nulls at a 1% significance level, respectively, suggesting a bilateral causality between EU stock market integration and EMU.

[Table 8 around here]

Yet, the traditional Granger causality method does not account for time lags on variables and size of the causality between variables as it is designed to deal with pairs of variables. So, for a matter of an elaborate study, we refine the Granger causality between them in Table 8 by employing the panel VAR method developed based on the traditional Granger causality method.

The results for this are clearly present in Table 9. First of all, the Johansen Fisher-panel cointegration statistics in Panel A of Table 9 do not reject the null of no cointegration between the two variables at all at any significance levels and then suggest that there is no cointegration between both. This result allows us to use the VAR method

[8]The specific are untabulated to save space but are available upon request.

for the Granger causality tests without any corrections on errors in the two time-series variables. The results obtained from the Panel VAR tests are presented in Panel B. Since the Hausman statistics do not reject the null for the two cases at standard levels and so, suggest a preference of the panel VAR models with random effects as the best fit for our panel data. So, we focus on the results obtainable from the panel VAR models with random effects. The two panel VAR tests in Panel B estimates significantly positive coefficients (0.238 and 0.073) on the first lagged EMU and Z_correlations for the pairwise respective dependent variables of the Z_correlations and EMU. The results are generally in line with ones of the traditional Granger causality test discussed already which suggest the bilateral causality between EU stock market integration and EMU. Importantly, the VAR test results in Panel B provide us with invaluable information about the amount of the Granger causality between the two variables. That is, although both significantly make bilateral causal relationship each other, each enogenous explanatory variable shows different sizes of coefficients. Specifically, the coefficient of the EMU_{t-1} variable (0.238) is much greater than that of the $Z\_correlations_{t-1}$ (0.073), suggesting that EMU makes a stronger predicting power for EU stock market integration.

[Table 9 around here]

The results that EU stock market integration does also Granger causes EMU even if the size of the Granger cause is less than the former case should be interesting in that EU stock market can further progress toward a coupling in this region by stimulating EMU. This may contribute to an establishment of a good circulation across the financial (stock) market development and the stabilisation of EMU in Europe. Moreover, this finding would give one not only meaningfully invaluable political but also practical implications for the current point of negative view about perspective of single currency (i.e., Euro) for financial market developments in Europe.

6. Conclusions

The principal aim of this paper is to investigate the impacts of EMU and monetary performance convergence on dynamic integration of European stock markets over the full sample period 1990-2014. As a proxy of EMU (convergence) this study uses inflation and interest rate differentials. As a proxy of stock market integration this paper uses time varying realised correlations. This study employs a panel data method to examine whether, on average, both the EMU launch and recent EU banking crisis have a positive effect on integration of EU stock markets.

The use of a slope dummy taking a value of 1 from 1999 onwards allows us to effectively examine whether an intercept shift (e.g., a variation in the average correlation, from 1999 onwards) and a slope coefficient shift (e.g. a variation in the impact of proxies of EMU convergence from 1999 onwards) have occurred. Both FE and RE models suggest, after 1st January 1999, a statistically significant increase in the mean value of realised correlation of stock returns. Regarding the effects of the recent EU banking crisis in 2010-2011, it also contributed to an increase in comovement of European stock markets. This would due to volatility spillover effects during the crisis periods rather than due to return spillover effects. The two panel models also indicate a statistically significant increase in negative relationships between the realised correlations and inflation differentials of the sample EU countries since the EMU launch. The finding related to the lower differentials in inflation rate strongly suggests that monetary convergence of inflation differentials among the EU countries has been a key driver for the increase in integration of European stock markets since then. Similarly, monetary convergence of interest rate differentials between the EU countries has made a negative impact on the integration post EMU. Overall, these empirical results obtained from this study for the post EMU periods supports our theoretical expectation argued for this study. Meanwhile no significant effect on integration of EU stock markets pre EMU is found in the two panel models. It is interesting that the Granger causality tests in this study suggest the bilateral causality between EU stock market integration and EMU.

In a nutshell, this study supports a positive impact of EMU on integration of European stock markets. Effective reforms of macroeconomic policy exert significant effects on the behaviour of stock investors. Accordingly, this study has invaluable implications for investors' diversification and for policymakers' conduction of a single monetary policy in Europe. In addition, this study targeting mostly western and northern EU countries could provide us with meaningful implications or lessons regarding the process of convergence of recently emerging central and eastern EU stock markets (Simon, 2005 and Van Beek et al., 2000 among others). Some limitations should be mentioned. This paper focuses on European stock market integration in a country level. It would be worthwhile to investigate nature and drivers of time-varying integration of European stock markets in an industry or firm level.

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Table 1. Descriptive statistics for exogenous independent variables

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Min	Median	Max	Obs.
InterestRateDifferentials (*InterDif*)	1.3581	2.3511	2.4385	9.0652	0	0.3	13.1	N = 2275 n=91 T = 25
InflationDifferentials (*InfDif*)	0.01603	0.0217	3.434198	17.4261	0	0.0093	0.1641	N = 2275 n=91 T = 25
IndustrialProductionDifferentials (*IP_Dif*)	0.1624	0.1575	1.2225	4.5127	0	0.1	0.8	N = 2275 n=91 T = 25
VDAX	20.2176	11.7026	0.4756	3.6289	0	17.91	51.13	N = 2275 n=91 T = 25
US3mTreasuryBill (*US-Tbill*)	3.1556	2.3006	-0.0248	1.7477	0.02	3.29	7.55	N = 2275 n=91 T = 25

Note. N, n and T denote the numbers of total observations, panel groups and years, respectively.

Table 2. IPS-panel unit root test results for the whole level variable

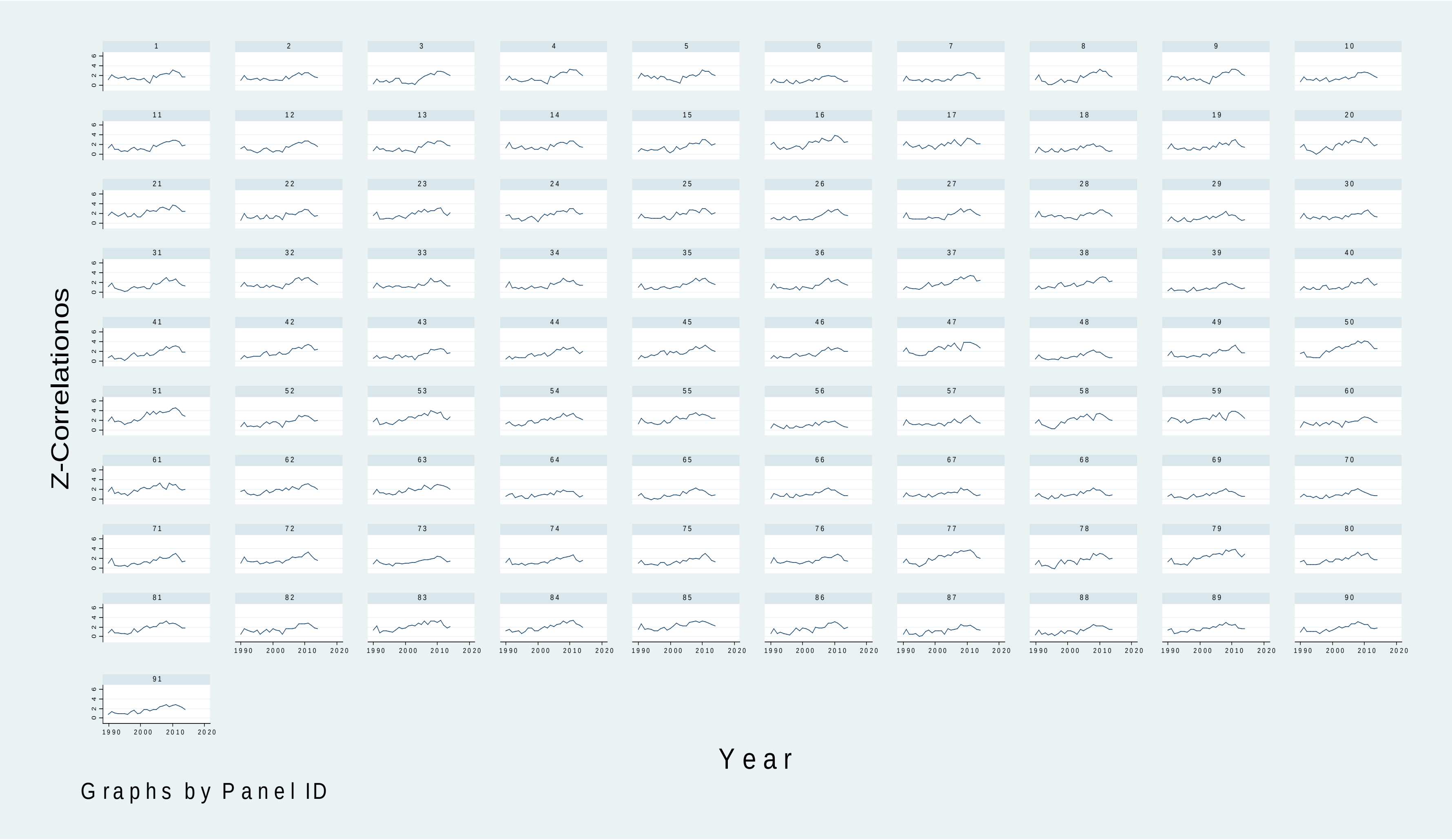
Variables	Level variable		
	H_0: Unit root		
	W-t-bar statistics	*p - value*	*lag*
Z_Correlation	-3.6993***	0.001	0.05
InterestRateDifferentials	-13.4403***	0.000	0.38
InflationDifferentials	-26.3438***	0.000	0.26
IndustrialProductionDifferentials	-40.6869***	0.000	0.24
VDAX	-15.6575***	0.000	0.00
US3mTreasuryBill	-7.1936***	0.000	1

***Notes**:* *** denotes significance at 1% level. Lags are averaged ones chosen by AIC for ADF regressions.

Table 3. Correlation matrix across the exogenous independent variables

	InterDif	*InfDif*	*IP-Dif*	*VDAX*	*US-Tbill*
InterestRateDifferentials	1				
InflationDifferentials	0.6649	1			
IndustrialProductionDifferentials	0.097	0.1224	1		
VDAX	-0.3426	-0.3246	-0.0322	1	
US3mTreasuryBill	0.0019	0.0005	0.0167	-0.021	1

Figure 1. Time varying (Z- Fisher transform) realised correlations



Note: Panel ID: 1: Austria–Belgium, 2: Austria–Denmark, 3. Austria–Finland 4: Austria–France, 5: Austria–Germany, 6: Austria–Greece, 7: Austria–Ireland, 8: Austria–Italy, 9: Austria–Netherland, 10: Austria–Portugal, 11: Austria–Spain, 12: Austria–Sweden, 13: Austria–UK, 14: Belgium–Denmark, 15: Belgium–Finland, 16: Belgium–France, 17: Belgium–Germany, 18 Belgium–Greece, 19 Belgium–Ireland, 20: Belgium–Italy, 21: Belgium–Netherlands, 22: Belgium–Portugal, 23: Belgium–Spain, 24: Belgium–Sweden, 25: Belgium–UK, 26: Denmark–Finland, 27: Denmark–France, 28: Denmark–Germany, 29: Denmark–Greece, 30: Denmark–Ireland, 31: Denmark–Italy, 32: Denmark–Netherlands, 33: Denmark–Portugal, 34: Denmark–Sweden, 35: Denmark–UK, 36: Finland–France, 37: Finland–Germany, 38: Finland–Greece, 39: Finland–Ireland, 40: Finland–Italy. 41: Finland–Netherland, 42: Finland–Portugal, 43: Finland–Spain, 44: Finland–Denmark, 45: Finland–Sweden, 46: Finland–UK. 47: France–Germany, 48: France–Greece, 49: France–Ireland, 50: France–Italy, 51: France– Netherlands, 52: France–Portugal, 53: France–Spain, 54: France–Sweden, 55: France–UK, 56: Germany–Greece, 57: Germany–Ireland, 58: Germany–Italy, 59: Germany–Netherlands, 60: Germany–Portugal, 61: Germany–Spain, 62: Germany–Sweden, 63: Germany– UK, 64: Greece–Ireland, 65 : Greece–Italy, 66: Greece–Netherlands, 67: Greece–Portugal, 68: Greece–Spain. 69: Greece–Sweden, 70: Greece–UK, 71: Ireland–Italy, 72: Ireland–Netherlands, 73: Ireland–Portugal, 74: Ireland–Spain, 75: Ireland–Sweden, 76: Ireland–UK, 77: Italy–Netherlands, 78: Italy–Portugal, 79: Italy–Spain, 80: Italy–Sweden, 81: Italy–UK, 82: Netherlands–Portugal, 83: Netherlands–Spain, 84: Netherlands–Sweden, 85: Netherlands–UK, 86: Portugal–Spain, 87:Portugal–Sweden, 88: Portugal–UK, 89: Spain–Sweden, 90: Spain–UK, 91: Sweden–UK.

Table 4. Results of static panel regressions for European stock market integration

Variables	Reg.1	Reg.2	Reg.3	Reg. 4	Reg. 5	Reg.6
Constant	1.048***	0.996***	1.379***	1.355***	1.379***	1.357***
	(0.026)	(0.021)	(0.059)	(0.101)	(0.103)	(0.101)
D_{EMU}	0.750***	0.854***	0.882***	0.972***	0.915***	0.977***
	(0.031)	(0.033)	(0.032)	(0.035)	(0.037)	(0.038)
D_{GIIPS}	0.954***	0.977***	0.903***	0.926***	0.936***	0.906***
	(0.030)	(0.027)	(0.035)	(0.028)	(0.030)	(0.029)
InterDif	0.001		-0.013		0.001	-0.012
	(0.001)		(0.006)		(0.008)	(0.008)
InterDif _D_{EMU}	-0.089***		-0.073***		-0.076***	-0.067***
	(0.011)		(0.013)		(0.012)	(0.013)
InfDif		2.037***		0.718	-0.382	1.176*
		(0.552)		(0.584)	(0.662)	(0.710)
*InfDif*_D_{EMU}		-10.467***		-7.390***		-8.520***
		(1.852)		(1.930)		(2.017)
IP_Dif			-0.020	-0.001	-0.019	0.009
			(0.075)	(0.074)	(0.074)	(0.074)
VDAX			-0.013***	-0.012***	-0.013***	-0.120***
			(0.001)	(0.001)	(0.001)	(0.001)
US-Tbill			-0.042***	-0.056*	-0.052*	-0.050*
			(0.013)	(0.031)	(0.032)	(0.031)
Number of observations	2275	2275	2275	2275	2275	2275
Number of groups	91	91	91	91	91	91
Correlation (δ_i, x_i)	0.013	-0.008	0	-0.013	0.004	0.022
R^2	0.353	0.342	0.398	0.382	0.390	0.403
Joint test	848.59***	971.99***	5289.000***	538.25***	437.14***	403.34***
$(F-value \text{ or } Wald-\chi^2_{(k)})$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	<1%	<1%	<1%	<1%	<1%	<1%

LM test($\chi^2_{(1)}$)	2290.44*** (0.000) <1%	2306.70*** (0.000) <1%	2203.53*** (0.000) <1%	2087.87*** (0.000) <1%	1863.32*** (0.000) <1%	1755.25*** (0.000) <1%
Hausman test($\chi^2_{(k)}$)	15.83*** (0.003) <1%	57.40*** (0.000) <1%	7.71 (0.360) > 10%	30.000*** (0.000) <1%	30.71 (0.000) <1%	205.51*** (0.000) <1%
Pesaran test	192.415*** (0.000) <1%	199.708*** (0.000) <1%	186.210*** (0.000) <1%	193.086*** (0.000) <1%	186.12***1 (0.000) <1%	185.915*** (0.000) <1%

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate robust standard errors. Sign denotes the expected coefficient sign. $F-value$ and $Wald-\chi^2_{(k)}$ are joint test values for the FE and RE models, respectively.

Table 5. Results of endogeneity bias test with instrumental variables

Variables	Reg.1	Reg.2	Reg.3	Reg. 4	Reg. 5	**Reg.6**
Constant	1.056***	0.985***	1.452***	1.424***	1.455***	1.425***
	(0.030)	(0.027)	(0.114)	(0.114)	(0.114)	(0.114)
D_{EMU}	0.743***	0.864***	0.908***	0.981***	0.902***	0.972***
	(0.034)	(0.035)	(0.036)	(0.036)	(0.036)	(0.039)
D_{GIIPS}	0.954***	0.977***	0.900***	0.920***	0.901***	0.901***
	(0.042)	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)
InterDif	0.003		0.002		-0.002	-0.022**
	(0.007)		(0.007)		(0.009)	(0-.009)
InterDif $\_D_{EMU}$	-0.091***		-0.074***		-0.069***	-0.054***
	(0.018)		(0.017)		(0.08)	(0.019)
InfDif		3.452***		2.162***	0.761	3.445***
		(0.788)		(0.784)	(0.894)	(1.029)
InfDif$\_D_{EMU}$		-11.685***		-8.328***		-10.417***
		(1.885)		(1.855)		(2.013)
IP_Dif			-0.018	-0.004	-0.024	0.003
			(0.072)	(0.073)	(0.072)	(0.072)
VDAX			-0.014***	-0.013***	-0.014***	-0.013***
			(0.001)	(0.001)	(0.001)	(0.001)
US-Tbill			-0.062*	-0.071**	-0.654*	-0.062*
			(0.035)	(0.035)	(0.035)	(0.035)
Number of observations	2184	2184	2184	2184	2184	2184
Number of groups	91	91	91	91	91	91
Correlation (δ_i, x_i)	0.010	-0.020	-0.021	-0.057	-0.031	0.005
R^2	0.445	0.450	0.484	0.484	0.484	0.039
$Wald-\chi^2_{(k)}$	21262.74***	21461.14***	22983.21***	15393.88***	15367.77***	15584.59***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	<1%	<1%	<1%	<1%	<1%	<1%

Instrumented variable(s)	1st lagged *InterDif*	1st lagged *InfDif*	1st lagged *InfDif*	1st lagged *InterDif*	1st lagged *InterDif & InfDif*	1st lagged *InterDif & InfDif*
Hausman test($\chi^2_{(k)}$)	107.27*** (0.000) <1%	928.28*** (0.000) <1%	140.00*** (0.000) <1%	2075.14*** (0.000) <1%	229.59*** (0.000) <1%	172.46*** (0.000) <1%

Notes: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parentheses indicate standard errors. Instrumented variables used in the endogeniety bias test are the first lagged *InflationDifferentials* and *InterestRateDifferentials* variables. The coefficients in the RE model are estimated by SGLS (2stages GLS) method.

Table 6. Results of FE models with Driscoll-Kraay standard errors

Variables	Reg.1	Reg.2	Reg. 4	Reg. 5	**Reg.6**
Constant	1.048*** (0.082)	0.996*** (0.064)	1.355*** (0.197)	1.379*** (0.195)	1.356*** (0.198)
D_{EMU}	0.750*** (0.242)	0.854*** (0.221)	0.972*** (0.188)	0.915*** (0.200)	0.976*** (0.197)
D_{GIIPS}	0.954*** (0.185)	0.977*** (0.196)	0.926*** (0.926)	0.906*** (0.158)	0.906*** (0.157)
InterDif	0.001 (0.021)	2.037 (1.55)		0.001 (0.017)	-0.012 (0.011)
InterDif $\_D_{EMU}$	-0.089*** (0.014)	-10.467*** (2.056)		-0.076*** (0.012)	-0.067*** (0.013)
InfDif			0.718 (2.446)	-0.382 (2.131)	1.177 (2.222)
InfDif$\_D_{EMU}$			-7.389** (3.040)		-8.520*** (2.665)
IP_Dif			-0.001 (0.171)	-0.019 (0.169)	0.009 (0.170)
VDAX			-0.012* (0.006)	-0.013** (0.006)	-0.012* (0.007)
US-Tbill			-0.056** (0.025)	-0.052* (0.027)	0.050* (0.026)
Number of observations	2275	2275	2275	2275	2275
Number of groups	91	91	91	91	91
(Within) R^2	0.461	0.463	0.491	0.492	0.197
Joint *F* test	326.39*** (0.000) <1%	370.42*** (0.000) <1%	258.58*** (0.000) <1%	255.53*** (0.000) <1%	206.51*** (0.000) <1%

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate Driscoll-Kraay standard errors.

Table 7. Results of dynamic panel regressions for European stock market integration

Variables	Reg.1	Reg.2	Reg.3	Reg. 4	Reg. 5	Reg.6
Constant	0.490***	0.454***	0.704***	0.697***	0.706***	0.702***
	(0.027)	(0.025)	(0.095)	(0.095)	(0.095)	(0.094)
Zorrelations$_{t-1}$	0.579***	0.576***	0.555***	0.555**	0.554***	0.550***
	(0.016)	(0.035)	(0.016)	(0.016)	(0.034)	(0.016)
D_{EMU}	0.264***	0.318***	0.391***	0.414**	0.388***	0.415***
	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)	(0.037)
D_{GIIPS}	0. 505***	0.521***	0.492***	0.504**	0.493***	0.497***
	(0 .027)	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)
InterDif	-0.001		-0.003		-0.005	-0.011
	(0.006)		(0.006)		(0.007)	(0.009)
InterDif $\_D_{EMU}$	-0.049***		-0.038***		-0.036***	-0.031***
	(0.010)		(0.010)		(0.012)	(0.012)
InfDif		1.501**		0.627	-0.418	1.300
		(0.725)		(0.717)	(0.824)	(1.010)
InfDif$\_D_{EMU}$		-4.468***		-2.256*		-3.410***
		(1.346)		(1.403)		(1.626)
IP_Dif			-0.067	-0.066	-0.071	-0.062
			(0.058)	(0.059)	(0.059)	(0.059)
VDAX			-0.010***	-0.009***	-0.010***	-0.009***
			(0.001)	(0.001)	(0.001)	(0.001)
US-Tbill			-0.014	-0.056*	-0.015	-0.015
			(0.028)	(0.031)	(0.028)	(0.028)
Number of observations	2184	2184	2184	2184	2184	2184
Number of groups	91	91	91	91	91	91
Correlation (δ_i, x_i)	0.387	-0.372	0.367	-0.348	0.3634	0.366
R^2	0.700	0.695	0.710	0.706	0.710	0.711
Joint *F* test	1132.80***	1190.83***	731.36***	746.45***	652.71***	591.35***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	<1%	<1%	<1%	<1%	<1%	<1%
LM test($\chi^2_{(1)}$)	7.02***	8.45***	12.76***	12.92***	9.86***	9.92**
	(0.008)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)
	<1%	<1%	<1%	<1%	<1%	<1%
Hausman test($\chi^2_{(k)}$)	1374.20***	136.56***	946.44***	155.11***	532.78***	209.62***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	<1%	<1%	<1%	<1%	<1%	<1%

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate robust standard errors.

Table 8. Pairwise Granger causality test between EU stock market integration and EMU

Null hypothesis (H_0)	Observations	F-Value	P-Value	
EMU does not Granger cause Z_correlations.	2093	113.455	0.000*** (<1%)	Rejection
Z_correlations does not Granger cause EMU.	2093	30.800	0.000*** (<1%)	Rejection

Note: ***denote significance at 1% level.

Table 9. The panel VAR tests for Granger causality between EU stock market integration and EMU

Panel A. Results of the Johansen Fisher panel cointegration test

H_0	Fisher statistics from trace test	Fisher statistics from max eigen test	Observations
No cointegration	92.61 (1.000)	114.5 (1.000)	2275
At most 1 cointegration	49.15 (1.000)	49.15 (1.000)	2275

Notes: Figures are p-values in the parenthesis. Probabilities are computed using asymptotic Chi-square distribution. A linear deterministic trend included. Lag interval (in first difference) is 1-1.

Panel B. Results of the panel VAR tests

Dependent Variable : Z_Correlations H_0: EMU does not Granger cause Z_correlations		Dependent Variable : EMU H_0: Z_correlations do not Granger cause EMU	
Constant	0.238*** (0.000)	Constant	-0.078*** (0.000)
Z_Correlationss$_{t-1}$	0.773*** (0.000)	EMU$_{t-1}$	0.876*** (0.000)
EMU$_{t-1}$	0.238*** (0.000)	Z_Correlationss$_{t-1}$	0.073*** (0.000)
Number of observations	2184		2184
Number of Groups	91		91
R^2	0.701		0.845
F - value	2557.935*** 0.000 (<1%)		5970.568*** 0.000 (<1%)
Hausman Statistics ($X^2_{(2)}$)	0.000 (1.000) (>10%)		0.000 (1.000) (>10%)

Notes: ***denotes significance at 1% level. Figures in the parenthesis are p-values.